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Bi-criteria risk analysis of domain-specific and cross-domain changes in complex systems

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ABSTRACT

Government and not-for-profit organizations measure success in terms of their ability to promote an organizational mission. Complex assets in such organizations are acquired in a budget-allocation process which reflects mission priorities. So, complex assets in such an environment must be managed so that availability of the asset is sufficient to support mission objectives as planned. But cost must also be contained within the budget plan, or other mission objectives may suffer. Hence, an objective in such environments is to simultaneously control (1) the risk that percent-availability will fall below a minimum planning threshold α, and control (2) the risk that cost will exceed the planned budget β. This problem is especially difficult because the two risks are negatively correlated.

In this paper we examine this bi-criteria risk minimization problem, for an organization in which the departments (domains) of the organization must compete for scarce resources to achieve organizational objectives. We develop a model that can be used to assess bi-criteria risk of single-domain proposals, and a ranking-and-selection procedure which can be used to choose between those proposals. We then conduct a limited search of solutions which involve linear combinations of the proposals, in order to investigate the potential benefits of 'breaking silos' and 'cooperation' across domains. Results suggest that for complex systems at least, cross-domain solutions are not always superior to single-domain solutions, and that integrated system models are needed to properly evaluate single-domain or cross-domain solutions.

1. Introduction

In managing productive assets, two key measures of effectiveness are Operational Availability (Ao) – the percentage of time the assets are available for productive operations, and the life cycle cost (LCC) – the net present value of the total ownership cost of the assets, from acquisition through retirement.

In the public sector, LCC is projected and approved in advance (planned and budgeted). Along with LCC, Ao is part of the design criteria of an asset (Hwang, 1996), and projected Ao becomes part of mission planning. Hence, after acquisition is approved and assets are in the field, asset managers have budgets and availability standards which must be maintained. As managing agents (stewards) representing risk-averse taxpayers, or simply to advance their own public sector careers, decision makers may be *primarily* concerned with reducing the risk that cost will exceed the budgeted plan, and reducing the risk that availability will fall below the promised planning threshold. We refer to these criteria as *cost risk* and *readiness risk*. In this paper we assume that good stewardship is synonymous with risk minimization.

The assets we examine in our numerical analysis are hypothetical fighter aircraft, F-XX (Kang & Doerr, 2012). The F-XXs are complex systems which require expenditures for a wide variety of personnel, parts, infrastructure and consumable resources. Their mission performance depends not only on operating personnel, but on the reliability of a collection of components, and a network of maintenance and supply associated with each of those components.

Capturing the LCC of such systems is not a trivial task. There are a large number of important exogenous factors involved, including the capital discount rate, and the price of petroleum, oil and lubricants. There are economies of scale in developing the support infrastructure for training personnel, and maintaining the aircraft. Likewise, modeling the factors which determine the Ao of a system such as the F-XX is daunting. Availability of the system depends on the availability of a number of critical components, each of which has a network of replacement parts and repair processes which must be tracked.

In this paper, we use a simulation model developed over several years as a decision support system to facilitate understanding of

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the relationship between Ao and LCC in a weapon system (Kang, Doerr, Apte, & Boudreau, 2010; Kang, Doerr, & Sanchez, 2006; Kang & McDonald, 2010). We extend that decision support tool to estimate readiness risk and cost risk, and then embed the tool in a search procedure. The search procedure examines a set of process-improvement scenarios to determine a Pareto Set of scenarios which (from the set of proposed solutions) jointly minimize cost risk and readiness risk. Our search procedure, and details of the relevant functional relationships are explained in detail below. The model and risk minimization (selection) procedure are contributions of this paper.

We examine scenarios across four logistics domains: Operations, Maintenance, Supply and Engineering (Re-)design. Each scenario is developed by one domain in isolation, and involves only variables under the control of that domain. We also develop a cross-domain alternative via a numerical search on linear combinations of the single-domain solutions. Our set of single-domain alternatives is developed to represent what have been called 'silos' (Lessard & Zaheer, 1996), which sometimes get created by the departments of a large public organization, and which make interdisciplinary efforts more difficult. It is commonly assumed that large savings can be obtained by breaking down these silos, and encouraging better cooperation. Another contribution of this paper is the examination of this assumption. We will show that although it may be true that cross-domain solutions are better, it is not trivially true. That is, single domain solutions may be surprisingly good, and better cross-domain solutions cannot be obtained simply, and perhaps cannot be obtained at all, without a tool such as the one we employ.

In the next section we review the related literature on improving LCC and Ao, the literature on risk management and silos in the public sector, and the literature related to our methodology.

2. Literature review

In this section, we review the literature relevant to our choice of criteria, and the underlying business problem relating to the tradeoff of those criteria. We examine the work that has been done to model closely related business problems. Finally, we briefly review the approaches that have been taken to solving similar bi-criteria risk-minimization problems.

2.1. Criteria

Focus on LCC as an effectiveness metric started at least as long ago as the 1970s, as organizations began to realize that, in the acquisition of technology-based assets, the price of acquisition was a fraction of the total ownership cost (Greenwall, 1977; Lientz, Swanson, & Tompkins, 1978). Recent estimates place Acquisition cost (including RDTE) at an average of 28% of LCC (Boudreau & Naegle, 2005). U.S. Department of Defense (DOD) interest in this metric has been keen from the outset (e.g., Lientz et al., 1978 was funded by the U.S. Office of Naval Research), even though LCC stretches across many budget cycles for most assets. Perhaps this is because some complex weapon systems have cost far more in retrospect than originally planned. The reduction of LCC is a stated DOD priority, and some authors have advocated incorporating LCC as a key design parameter in the initial stages of weapon system development (Boudreau & Naegle, 2005).

While perhaps less well known in the Private Sector, Ao has an even longer history as a key metric in the Public Sector, and the DOD in particular, dating at least as far back as the late 1950s (Bovaird, Goldman, & Slattery, 1962). For non-for-profit organizations, Ao provides a surrogate metric for the profit (benefit) gained through possession of a productive asset (that is, the percentage of time the asset is *available* to support the non-profit mission has been used as a surrogate for the contribution of that asset *to* the mission). Within the U.S. Armed Services, the use of Ao is pervasive, even to the point of measuring labor productivity via its impact on Ao (Horowitz & Sherman, 1980).

Hundreds of papers have been written using either Ao or LCC as criteria: a comprehensive review of either literature is beyond the scope of the current research. The modeling of a bi-criteria tradeoff between availability and cost is more recent. Mostly, these tradeoff models (e.g., Level-of-Repair-Analysis) examine spare inventory levels, and the availability of parts, but they do not incorporate system-level availability as a criterion. Also, these models do not examine LCC at the system level, but rather capture only that part of operations & maintenance cost directly affected by the decision variables they model (i.e., echelon inventory and repair costs). As we will show, such approaches cannot model the impact of operational decisions on *system* cost and availability, because spare parts availability is only part of the determinant of system availability, and operations and maintenance costs are only a part of systems cost. Our goal in this paper is to capture the impact of resource allocation decisions on system availability and system cost *risk*. Large scale simulation models (reviewed in the next subsection) have been built in recent years which capture the system-level tradeoff between LCC and Ao, but these models examine average LCC and Ao as criteria, rather than risk.

2.2. Business problem

As will be detailed in Section 3 of this paper, the Ao of a complex system is determined by several underlying factors for each component of that system. All of these underlying factors are variable, and a complex system has a large number of components (and critical parts within those components), so the modeling of the impact of even one factor (e.g., reliability) on system-wide Ao is a stochastic combinatorial problem. Similarly, the LCC of a complex system is determined by a large number of fixed and variable costs, many of which also affect Ao. Consequently, to our knowledge, no analytical model has ever been developed (or at least, none has ever been solved) which captures both Ao and LCC as optimization criteria in a complex system.

In recent years, analytical cost-based models have appeared to capture some one of the underlying factors of Ao (especially reliability or inventory). An example of this is Majety, Dawande, and Rajgopal (1999) which solved a problem allocating constrained budget dollars to components in order to maximize reliability. Work continues in this vein, for example Coelho (2009) uses a hybrid meta-heuristic/MIP approach to solve a similar problem, while Moreb (2007) solves a deterministic version of the problem using integer programming.

Some work has appeared which optimizes Ao, subject to a cost constraint, or minimizes LCC subject to constraints on Ao. For example, Jin, Yeo, Chung, and Kim (2003) optimize average 'unavailability' (1-Ao) of jacketed reactors (used in power generation) subject to a cost constraint using an integer program. Conversely, Bouachera (2012) developed a model to minimize the LCC of gas turbine systems, subject to constraints on Ao.

Descriptive modeling work has appeared, based mostly on large scale simulations, which predicts the Ao and LCC of complex systems. Mostly, this work has been intended for decision support and what-if analysis of particular large scale systems. An early example of this is the work of Stalnaker (1993) who developed a predictive simulation for use at NASA (but made available for general use). Another is the work of Slay et al. (1996) developed on contract for the U.S. Air Force. To our knowledge, neither of these simulations was ever used in formal descriptive research. However, Hwang (1996) developed a simulation model to support the examination of design alternatives in terms of LCC and availability. And Kang et al. (2006) report on a formal study using a Nearly Orthogonal Latin Hypercubes design, which identified the factors of fuel price and number of flight hours as primary LCC drivers for an Unmanned Aerial Vehicle, while preventive maintenance lead time was found to be a primary driver of Ao. This work was extended by Kang and McDonald (2010) to the Light Armored Vehicle with a 25 mm Gun System (LAV-25) case study. In this case study the number of operating hours, and reliabilities of major components were found to be the most critical factors for both LCC and Ao.

Wang and Sivazlian (1997) developed a model to compare two systems in terms of their cost-benefit ratio, where benefit was defined in terms of availability and cost was defined as total life cycle cost. But the systems they examined were not complex, and they did not examine risk.

McGee, Rossetti, and Mason (2005) developed a simulation model to quantify the impact of transportation policies on Ao for military supply chain of spare parts and the total transportation cost. Then they applied the response surface analysis to develop regression equations for Ao and the total transportation cost in terms of the factors for the transportation policy (e.g., sortie frequency, sortie duration, etc.).

The recent interest in Performance Based Logistics (PBL) can be seen in part as recognition that Ao and LCC need to be considered jointly, as these are key metrics in most PBL contracts (Doerr, Lewis, & Eaton, 2005). In PBL contracts, an organization provides logistics outcomes which must be met to a vendor, but allows the vendor to determine the best method of delivering those contracted metrics. Since the outcomes almost always include LCC and Ao, this literature contains work relevant to our problem.

Much of the recent academic work in PBL takes the vendor's perspective. In Kim, Cohen, and Netessine (2011) and Mirzahosseinian and Piplani (2011), vendors are given a PBL contract for availability and may choose to improve reliability of components rather than increase spare inventory levels in order to reduce their own costs. Nowicki, Kumar, Steudel, and Verma (2008) and Mirzahosseinian and Piplani (2011) both model a (vendor) profit-maximizing problem, given the PBL-contracted Ao metrics as a constraint. Two papers in the PBL literature take a game theoretic (supply chain) perspective, examining ways to set contracted metrics which incentivize the desired behavior from the vendor (Ferguson & Sodhi, 2011; Kim, Cohen, Netessine, & Veeraraghavan, 2010). To our knowledge, only the paper by Kang et al. (2010) takes the contracting organization's (DOD's) perspective in examining PBL situations. They examine a set of proposals for improving Ao and reducing LCC, and develop a decision support system to help the contracting organization understand the tradeoffs. However, none of the literature in PBL examines the bi-criteria risk problem we model in this paper, and none examines the comparison of single-domain and cross-domain (silo breaking) solutions as we do in this paper.

2.3. Silos and risk in the public sector

At least since Lawrence and Lorsch (1967) there has been an awareness of the difficulties of what are called *silos* in large organizations. A silo is a semi-autonomous domain (a department or business unit) of an organization. The term is used in a pejorative way, to mean that the department is being managed in a way which optimizes its own local outcomes, at the expense of the other 'silos' of the organization. This competition can actually be encouraged (intentionally or not) by the incentives of the organization, or the way resources or allocated across departments. Once such silos are in place, some research suggests that valued incentives and formal processes must be in place to facilitate cooperation, or cross-domain efforts are likely to fail (Lessard & Zaheer, 1996). In this paper, we demonstrate how our model can be used as a part of that formal process of examining cross domain solutions.

In very large organizations, the departments in charge of various aspects of logistics can form their own silos: maintenance, supply, engineering and operations. A manager of a complex system depends on each of these functions to deliver availability at a low cost. To our knowledge, there is no research which seeks to quantify the negative impact of silos in logistics efforts to reduce costs or improve availability for complex systems. Recent work (and received wisdom) suggests that improvements from the Engineering Design domain to improve reliability may be in general more cost effective than increases in inventory supply to improve Ao (Kim et al., 2011). Of course, this does not mean that spare parts can be eliminated, or that efforts to improve availability should be directed to improving reliability alone. But it does suggest that the negative impact of silos in a particular problem may be less than one would expect, based on the negative rhetoric about silos.

In the current paper, we compare single-domain solutions to a cross domain solution in order to conduct a limited exploration of the magnitude of the negative impact of silos.

Public management decision making also exhibits excessive risk aversion in some cases (Meier, Gill, & Waller, 2000). Explicit measures of outcome risk have been recommended by public management researchers, so that the 'cost of being wrong' is 'not exogenous to the decision' (Gill & Meier, 2000). In spite of the large amount of public funds spent on complex assets such as weapons systems, very little research incorporates measures of either cost risk, or readiness risk. Exceptions to this include the work of Miman and Pohl (2006) who examined alternatives for reduction of cost risk, and Kang et al. (2010) who examined readiness risk in a post hoc analysis. To our knowledge, no research has examined bi-criteria minimization of Ao and LCC risk, though there is research on the bi-criteria minimization of other types of risk.

2.4. Previous approaches to related Bicriteria problems

In this research, we use simulation to select a bi-criteria optimal solution from a discrete set of scenarios. This immediately presents us with two methodological issues. First, there are a large number of methods for multiple criteria decision making, but (despite the advocacy of many authors for their favorite approach) no simple way to prescribe the choice between those methods. Second, in stochastic problems, multiple criteria decision problems are more difficult because appropriate definitions of stochastic dominance for each criterion must be established.

In reviewing multi-criteria methods used in simulation research, Rosen, Harmonosky, and Traband (2008) build a typology of methods which depend upon the timing of cross-criteria preferences from the decision maker: a priori choice (including traditional multi-attribute utility, and goal programming approaches), progressive disclosure (including Bernoulli's multi-attribute value function approach), and no preference (ranking and selection). They note that they were unable to find any examples of posterior ranking, perhaps 'because of the computational intensity that would be involved' in generating the state space of solutions. For this same reason, they recommend that ranking and selection procedures be used when the number of potential solutions is small.

Our criteria are both proportional risk measures, as detailed in the modeling section. While not unique, the use of risk measures as criteria in multi-criteria decision making is rarely seen. One example is Ravindran, Bisel, Wadhwa, and Yang (2010), who uses a goal programming approach for a supplier selection problem.

Our approach is to generate a Pareto Set of non-dominated solutions. Of course, there is no guarantee that this will provide a unique solution. So, we had planned to solicit criteria preferences via a simple multi-attribute ranking technique (e.g., SMART; Barron & Barrett, 1996) a posteriori to accomplish final ranking and selection. This approach would have been feasible because our set of alternatives is so small. However, as shown in our results, we did not encounter any situation in which the Pareto Set contained more than one solution, so the a posteriori ranking was not needed.

In determining the non-dominated set of alternatives, we use the approach of Teng, Lee, and Chew (2010) incorporating indifference zones. However, as will be described in the model section, we extend this concept to proportional risk estimates rather than mean estimates.

In the next section, we review the LCC and Ao model in more detail, and develop our approach to ranking and selection.

3. Model

In this section, we present a model of LCC and Ao for a complex asset class. By asset class, we mean a fleet of assets of the same sort. In other words, we are not modeling the isolated cost of owning a single asset, but rather, the cost of deciding to own a particular kind of productive asset. We model the ownership cost at this level so that we can appropriately track certain fixed costs, and economies of scale, based on the number of individual assets we choose to acquire and maintain.

The model is presented in two parts, but the functional relationship between LCC and Ao will be made plain through the shared factors which determine them.

3.1. LCC model

We model LCC as a function of 5 factors: (1) Operations & Maintenance (O&M), (2) Research, Development, Test and Evaluation & Acquisition, (3) Training, (4) Personnel, and (5) the discount rate needed to compute the present value of future expenditures. Each of these factors except the discount rate is a function of several other variables. Although we will only manipulate O&M variables directly in our scenarios, cost risk is a function the other factors as well. We will be evaluating alternatives in terms of their ability to reduce cost risk. Hence, the other factors must be incorporated in the model for the sake of completeness. By incorporating these other factors, we can also examine the limited leverage that can be applied to reduce cost risk, by changing O&M variables alone.

Let

$X_i^{[O]}$ = O&M cost for year i,
$X_i^{[R]}$ = RDTE & Acquisition costs for year i,
$X_i^{[T]}$ = Training cost for year i,
$X_i^{[P]}$ = Personnel cost for year i, and
r = the discount rate.

Then,

$$E[\mathrm{LCC}] = E\left[\sum_i \frac{X_i^{[O]} + X_i^{[R]} + X_i^{[T]} + X_i^{[P]})}{(1+r)^i}\right]$$

Our intent in this paper is to compare the impact of logistics improvements in separate logistics domains against the impact of a cross-domain improvement. Logistics improvements primarily impact LCC through O&M costs, and so we will formulate a detailed model of $X_i^{[O]}$ below. The other costs in the model primarily act as leverage factors. In this paper we will not detail every aspect of factors 2–5 which are incorporated in our simulation model. But we will briefly review these other factors, and give their magnitude in Section 4, so that the reader has the sense for the complexity of the problem. The reader interested in more detail on the other costs is referred to Kang and Doerr (2012).

O&M costs are important, but they are not usually the majority of LCC. In the Status Quo Scenario described in Section 4, O&M costs determine 32% of total costs. Moreover, not all O&M costs are affected by the changes we make in the scenarios, and we will not explicitly include those costs in our model formulation which are not affected by our decision variables. In particular, one-time costs associated with installing and disposing of the assets make up 1.1% of O&M costs (0.4% of LCC), Operations facility overhead makes up 12.4% of O&M costs (4.0% of LCC) and routine preventive maintenance costs make up 32.2% of O&M costs (11.2% of LCC). But none of these three are affected by the changes we examine in our scenarios. Again, readers interested in more detail on these aspects of O&M costs are referred to Kang and Doerr (2012). This leaves a total of 54.3% of O&M costs in the Status Quo scenario (17.3% of LCC in the Status Quo scenario) which are affected by (but cannot be eliminated by) the changes we examine.

Now, O&M costs include all fixed (amortized) and variable costs associated with using the asset, and keeping it in a usable state, except labor. A key factor in O&M cost is the number of echelons in supply and maintenance which will be established. In the scenarios described in Section 4, we assume costs will be incurred at 2 facilities, where the asset is used. But a complex asset almost always requires at least one additional level of support at which expensive maintenance equipment and expertise is centralized. In the scenarios described in Section 4, we model a single D-level facility which supports all asset requirements.

In the development below, when we say ‘a controllable variable’ we mean a random variable whose *parameters* we will change in our scenarios as a model of an *investment in process improvement.* Details of the specific changes will be given at the end of this section. On the other hand, when we say an ‘exogenous random variable’ we only mean the parameters of the variable are exogenous to the changes *we* will model, not necessarily that the variable is always exogenous to the management of the system.

The changes we examine affect three categories of O&M cost: consumable supplies cost (including fuel), transportation cost for parts and supplies, and non-routine maintenance & repair cost (associated with breakdowns or performance degradation). Let,

$$Y_i^{[C]} = \text{Operating consumable supplies cost for year}$$
$$i = aC^{[o]}H$$

where a is the total assets deployed (at all facilities), a constant; H is the number of hours each asset is in use per year, a controllable variable, and $C^{[o]}$ is the variable operating cost per hour, an exogenous random variable.

$$Y_i^{[T]} = \text{Parts and Supplies Transportation cost for year}$$
$$i = aC^{[t]}\sum_j F_j$$

where F_j is the number of component failures of component j in an asset in year i, a function of several random decision variables (described below), and $C^{[t]}$ is the variable transportation cost per hour, an exogenous random variable.

$$\begin{aligned} Y_i^{[R]} &= \text{Non-routine repair and maintenance cost for year } i \\ &= \text{cost of maintaining spare pool, plus cost of repair} \\ &= Z_i^{[s]} + Z_i^{[r]}, \text{cost of spares and repair, as described below} \end{aligned}$$

Now, for each component j, we assume the number of failures is distributed according to a Poisson distribution. So the Poisson inverse function $P^{-1}(L, E[F_j])$ will give us the expected number of spares required for an asset, given the desired protection level L, and the expected number of failures for that component, $E[F_j]$. A protection level L is the percentage of demand we intend to service via the spare pool, rather than awaiting repair. For parsimony, we will assume the protection level is the same for all components. Hence,

$$Z_i^{[s]} = h\sum_j C_j^{[s]} P^{-1}(L, E[F_j])$$

where h is the inventory carrying rate for the spares in inventory, a constant, and $C_j^{[s]}$ is the purchase cost of the spare component, which we treat as a controllable variable. The number of spares required for component j will be modeled as a random variable through L and F_j, both of which we treat as controllable variables.[1]

Since F_j is distributed according to a Poisson distribution, we have

$$E[F_j] = a\lambda_j T_j^{[m]}$$

where $T^{[m]}$ is the depot maintenance time, a controllable variable, which for parsimony we will assume is the same for all components, and λ_j is the failure rate of component j per operating hour (assuming one component per asset) which we also model as a controllable variable.

The repair cost also depends on the failure rate of the components, though in a simpler way;

$$Z_i^{[r]} = a\sum_j C_j^{[r]} H\lambda_j$$

where $C_j^{[r]}$ is a per-repair depot cost which we model as a controllable variable.

Finally, we have

$$\begin{aligned} X_i^{[O]} &= K + Y_i^{[C]} + Y_i^{[T]} + Z_i^{[s]} + Z_i^{[r]} \\ &= K + aC^{[o]}H + aC^{[t]}\sum_j F_j + r^{[s]}\sum_j C_j^{[s]} P^{-1}(L, a\lambda_j T_j^{[m]}) + a\sum_j C_j^{[r]} H\lambda_j \end{aligned}$$

where K is an exogenous random variable representing the portion of the O&M cost factors unaffected by the logistic changes we model in this paper, as outlined above.

3.2. Ao model

The simplest definition of Operational Availability is just

$$E[\text{Ao}] = E\left[\frac{\text{Time Asset Available}}{\text{Total Time}}\right]$$

We assume the productive assets in our model are meant to be available 365 days per year, and so total time is a constant. We assume a system will be available unless it is down for unplanned maintenance, preventive maintenance, or has been inducted into the component improvement program for major refurbish. So,

$$E[\text{Ao}] = \frac{E[\text{Total Time} - T^{[m]} - T^{[p]}]}{\text{Total Time}}$$

where $T^{[p]}$ is the total time required for preventive maintenance and component improvement program, an exogenous random variable. This means that our managerial leverage to improve Ao depends on $T^{[m]}$,

$$E[T^{[m]}] = E\left[(t + (1-L) * T^{[r]})\sum_j F_j\right]$$

where t is the faulty component swap time that we treat as a constant and $T^{[r]}$ is the depot repair time, a controllable variable.

3.3. Objective function and dominance criteria

Our objective is to

$$\text{Minimize}_{\mathcal{S}}\{P_s(A_o < \alpha), P_s(\text{LCC} > \beta)\}$$

where α is the minimum level of availability we rely upon in our mission planning, and β is the maximum life cycle cost to which we have committed in planning and budgeting. In our scenarios in Section 4, α is 75%, and β is \$6.5 billion. $P(A_o < \alpha)$ is what we have called readiness risk, and $P(\text{LCC} > \beta)$ is what we have called cost risk. $\mathcal{S}$ is the set of scenarios, or alternatives available. In each scenario $s \in \mathcal{S}$, the parameters of the controllable variables outlined in the previous two sections will change. And hence, in each scenario, A_o and LCC will have different distributions.

As noted above, we will use indifference zones (Teng, Lee, et al., 2010) to establish a Pareto Set of alternatives. For either criteria, if

$$|P_i(\blacksquare) - P_j(\blacksquare)| \leqslant \varepsilon$$

we will say that scenarios s_i and s_j are ε-equivalent for that criteria, and if

$$P_i(\blacksquare) - P_j(\blacksquare) > \varepsilon$$

we will say that scenario s_j ε-dominates scenario s_i for that criteria.

When ranking two scenarios across criteria using indifference zones, there are three kinds of outcomes:

Dominance. Scenario s_i may dominate scenario s_j, which (since we are minimizing) we write as $s_i \prec_{iz} s_j$. We say $s_i \prec_{iz} s_j$ when scenario s_i is ε-equivalent to s_j on one criteria, but ε-dominates s_j on the other criteria. Conversely, scenario s_j may dominate scenario s_i.

Indifference. We may be indifferent between the scenarios, which we write as $s_i \approx_{iz} s_j$. This happens when alternative s_i is ε-equivalent to alternative s_j on both criteria.

Pareto Equivalence. Finally, we may be unable to choose between the scenarios without weighting the criteria, which we indicate by writing $s_i \equiv_{iz} s_j$, in which case both scenarios are elements of the Pareto Set. This happens when s_i ε-dominates s_j on one criteria, but s_j ε-dominates s_i on the other criteria.

Since our criteria involve random variables, there is some probability that in implementation, the scenario we choose will yield inferior results to another scenario. Teng, Chew, Teng, and Goldsman (2010) developed a procedure to calculate the probability that one scenario is better than another (or at least, the probability that the difference was due to more than chance) when indifference zones are used. But in their case the criteria were independent, while in our case Ao and LCC are correlated. To develop a procedure to test for dominance with indifference zones when criteria are correlated, we extend the procedure of McNemar (1947), who provides a method of testing for differences in correlated proportions (but without indifference zones). To begin, we note that there are nine possible ways to achieve the three kinds of outcomes outlined above:

$$\begin{matrix} (s_{i,1} <_\epsilon s_{j,1}; s_{i,2} <_\epsilon s_{j,2}) & (s_{i,1} <_\epsilon s_{j,1}; s_{i,2} \approx_\epsilon s_{j,2}) & (s_{i,2} <_\epsilon s_{j,2}; s_{i,2} >_\epsilon s_{j,2}) \\ (s_{i,2} \approx_\epsilon s_{j,2}; s_{i,2} <_\epsilon s_{j,2}) & (s_{i,2} \approx_\epsilon s_{j,2}; s_{i,2} \approx_\epsilon s_{j,2}) & (s_{i,2} \approx_\epsilon s_{j,2}; s_{i,2} >_\epsilon s_{j,2}) \\ (s_{i,2} >_\epsilon s_{j,2}; s_{i,2} <_\epsilon s_{j,2}) & (s_{i,2} >_\epsilon s_{j,2}; s_{i,2} \approx_\epsilon s_{j,2}) & (s_{i,2} >_\epsilon s_{j,2}; s_{i,2} >_\epsilon s_{j,2}) \end{matrix}$$

All the cells of this matrix except the off-diagonal entries represent some form of dominance outcome. The upper triangle, cells (row 1, column 1), (1,2) and (2,1) are those that correspond to $s_i \prec_{iz} s_j$. The lower triangle of cells (2,3), (3,2) and (3,3) are those that correspond to $s_j \prec_{iz} s_i$. In the off-diagonal, the center cell (row 2, column 2) is the indifference outcome $s_i \approx_{iz} s_j$, while cells (1,3) and (3,1) are the Pareto Equivalence outcomes corresponding

[1] We are not attempting to define an optimal spare-inventory policy. Except as a source of process improvement, inventory policy is irrelevant to our research objectives, and is held constant across the scenarios in Section 4. One process improvement scenarios will look at inventory cost reductions, but the mechanism by which that reduction is accomplished is not via the implementation of an improved inventory policy.

to $s_i \equiv_{iz} s_j$. We use our simulation model to calculate probability estimates for each of the nine cells above, and enter the probability in the appropriate cell. We refer to this completed matrix of the outcome probabilities as $\mathcal{O}$.

We construct another outcome probability matrix assuming the scenarios are equivalent for a given value of ε. We refer to the matrix constructed assuming equivalence as $\mathcal{E}$. To test whether the two scenarios are significantly different, we could compare $\mathcal{O}$ to $\mathcal{S}$ using a χ^2 test. However, by summing the probabilities associated with each kind of outcome, we can reduce the matrix to a 2×2 contingency table and test for dominance using McNemar's (1947) test:

$$\begin{array}{ll} s_i \approx_\varepsilon s_j & s_i \prec_\varepsilon s_j \\ s_j \prec_\varepsilon s_i & s_i \equiv_\varepsilon s_j \end{array}$$

McNemar (1947) showed that the squared difference between the off-diagonal entries in such a matrix is distributed according to a χ^2 distribution with 1 degree of freedom. This approach controls for correlation because it does not incorporate the main diagonal entries which would be inflated by correlation. In our case, the negative correlation between criteria will tend to inflate the number of solutions in the Pareto Equivalence cell, while ε (as it increases) will tend to inflate the number of solutions in the indifference cell.

In the next section, we develop in detail a single set of scenarios to demonstrate our model, and to investigate the relative quality of cross-domain solutions in those scenarios.

4. Numerical analysis

In this section, we conduct a numerical analysis of our model on sets of sample scenarios. Each of the scenarios in a set involves changing variables from a single domain in logistics: Supply, Maintenance, Operations, and Engineering Redesign. The scenarios are not meant to represent the 'best' that can be done from within each of these domains: we are not comparing the relative importance of the logistical domains.

Our point is rather to compare particular single-domain solutions with a cross-domain solution comprised of a linear combination of those same scenarios. The management literature (Lawrence & Lorsch, 1967; Lessard & Zaheer, 1996) and received wisdom is that cross-domain solutions are better than single-domain, or 'silo' solutions. However, because the independent variables in the scenarios have an interactive and non-linear impact on the criteria, and because the criteria are themselves correlated, linear combinations of the single-domain solutions may perform better or worse than the single domain solutions, and this is a phenomenon we wanted to investigate more closely.

4.1. Performance improvement scenarios

Our numerical analysis will be based on the comparison of five scenarios for process improvement for a major weapon system, the F-XX fighter aircraft. The aircraft is deployed in 2 squadrons of 12 aircraft each, and the program operates a single depot for support. Details of model assumptions for the Status Quo scenario are given in Table 1. The values and distributions chosen in Table 1 are hypothetical, but those values have been reviewed for face validity by subject matter experts, and are similar in relative magnitude to other systems the authors have seen.

In the scenarios we develop here, senior leadership from each logistics domain has been asked to suggest an improvement that might be made to their own domain with a cash infusion of no more than \$10,000,000. This represents only about 0.1% of the expected undiscounted LCC of \$6.4b, but given tightly constrained budgets, this is the maximum cash infusion available to fund process improvement. When discussing LCC reduction efforts, Boudreau and Naegle (2005) point out that in many programs cost-reduction alternatives exist which cannot be pursued because of a lack of budget for the initial outlays. Leadership has been told that (in spite of the correlation between LCC and Ao) each improvement must simultaneously improve Ao, and reduce LCC. The domain-specific improvements are given in Table 2.

Table 1
Status Quo assumptions for O&M cost ($X_i^{[o]}$) and Ao.

Variable	Value/distributional assumption
a	24 aircraft
$C^{[o]}$	\$2000/h
H	~Uniform(57, 63) h/month
$C^{[t]}$	~Normal(\$200,\$20)
$C_1^{[s]}$	~Triangular(\$90,000, \$100,000, \$110,000)
$C_2^{[s]}$	~Triangular(\$225,000, \$250,000, \$275,000)
$C_3^{[s]}$	~Triangular(\$360,000, \$400,000, \$440,000)
$C_4^{[s]}$	~Triangular(\$450,000, \$500,000, \$550,000)
$C_5^{[s]}$	~Triangular(\$360,000, \$400,000, \$440,000)
$C_6^{[s]}$	~Triangular(\$1,800,000, \$2,000,000, \$2,200,000)
L	~Uniform(73%, 97%)
λ_j	~Triangular(1/175, 1/350, 1/700) failures/h (for j = 1, 5)
λ_6	~Triangular(1/150, 1/300, 1/600) failures/h
$T_j^{[r]}$	~Triangular(20, 40, 80) days $\forall j$
$C_j^{[r]}$	~Triangular(\$2500, \$5000, \$10,000) $\forall j$

Note that in the Design Engineering scenario the coefficient of variation (COV) of the decision variables is unaffected by the improvement. In the Operations scenario, COV of the decision variables is actually increased, because the plan involves a change in usage patterns that decreases usage slightly during regular operations, but significantly increases flight hours immediately before mission deployment. In the maintenance scenario, COV is cut in half, because mean performance is not changed. Finally in the Supply scenario, COV is also reduced, because prepositioning creates not only an improvement in the average supply time for spare parts, but also reduces the variability in lead time. Hence, our four scenarios involve: improvements in average performance but no change in variance, improvements in average performance but an increase in variance, no change in average performance but a decrease in variance, and improvement to both average performance and variance.

Counting Status Quo as a scenario, this gives us 5 scenarios to simulate, but a sixth scenario is also developed by examining simultaneous changes to (linear combinations of) the changes in all four domains. We refer to this sixth scenario as the cross-domain scenario.

It might be thought that changing all the variables at once is a simple and obviously superior scenario, but it is not necessarily the case. Notice that the impacts of these changes on the dependent variables are not independent. For example, a reduction in flight hours also reduces the impact of improvements in Protection Level. Also, note that the changes have non-linear impacts on the dependent variables. So, for example, a 20% change in engine Mean Time Between Failure (MTBF) from 300 to 360 h yields less than 20% of the improvement in Ao that a change in MTBF from 300 to 600 h yields.

Finally, since we developed each of the four domain-specific scenarios by assuming an infusion of \$10 m was available, it would hardly be a fair comparison to assume in our sixth scenario that all four changes could be made fully and simultaneously. A more fair comparison is to construct our sixth scenario by taking 25% of the improvement from each domain. As we will show, a cross domain scenario constructed by simply allocating 25% of each of the four domain-specific changes provides a smaller increment to Ao, *and* a smaller LCC reduction than other domain-specific alternatives.

Table 2
Domain-specific performance improvement scenarios.

Domain	Improvement
Design Engineering	Increase MTBF of six primary components by 100 h (reduce λ_j) through implementation of known but unfunded Engineering Change Orders
Operations	Reduce flight hours H from 60 to 56 h per month through increased use of simulators for training, supplemented with more intense hands-on experience immediately before mission
Maintenance	Cut variability (standard deviation) in T_m and $C_j^{[r]}$ in half through a fixed investment in capacity
Supply	Increase L (protection level) from 85% to 90%, simultaneously reducing $C^{[s]}$ by 20% through PBL agreements with vendors that involves purchasing more spares and more efficient inventory prepositioning, and in which cost reductions for the vendor are shared through price reductions to the organization

4.2. Results

First, we will find the best (Pareto Set) Single Domain solutions using $\varepsilon = 1.0\%$. Next we will examine a cross domain solution involving equal allocation of resources across the domains (same percentage of each of the four solutions) to find an equal-resource cross-domain solution which is superior to the 1%-ε optimal single-domain solution. Finally, we will conduct a limited search for cross-domain solutions which are superior to the best single-domain solution, but do not involve an equal allocation of resources across domains.

Solutions are obtained using Monte-Carlo simulation on the model developed in the previous section. Each scenario is run through the simulation for $n = 150{,}000$ iterations. In 50 simulated replications of the Status Quo scenario (test–retest reliability), this run size provided solutions to both criteria which never varied by more than 1%, the smallest value of ε we considered to have any practical significance.

4.2.1. Single-domain solutions

Table 3 shows the solutions provided by the single domain scenarios.

Note that each of the scenarios reduces LCC and increases in Ao when compared to the Status Quo. The smallest improvements are from Maintenance, which still provide a $28,088,270 cost reduction, and a 0.7% improvement in Ao. Each scenario also reduces risk compared to the Status Quo. The largest cost risk reduction comes from the Engineering domain, which reduces cost risk by 3.28%, and the largest readiness risk reduction comes from the Supply domain, which reduces readiness risk by 16.55%. Again, the comparison between domains is not meant to be generalizable: these are just example scenarios. The point here is just that each scenario 'works', in the sense that each scenario improves both average performance and reduces risk, but each scenario provides different rates of improvement across the performance averages and risk criteria.

The 1%-ε solution is the Supply scenario. On the criteria of readiness risk, Supply dominates all other scenarios by more than 1%. On the criteria of cost risk, Supply is 1%-ε equivalent to Operations and Engineering, and dominates other scenarios by more than 1%. Although the cost risk is slightly greater for the Supply scenario than the Engineering scenario, our test for dominance indicates Supply $\prec_{iz}$ Engineering ($\chi^2_{df=1} = 150.3$, $p < 0.000$). The Supply scenario provides a risk of 3.95% ($CI_{(.95)} = [3.85\%, 4.05\%]$) that LCC will exceed $6.5 billion, reduced from a cost risk of 6.46% in the Status Quo. It provides a risk of 4.49% ($CI_{(.95)} = [4.39\%, 4.60\%]$) that Ao will fall below 75%, reduced from a readiness risk of 21.04% in the Status Quo.

Note that the Supply scenario neither maximizes Ao (which is done by Engineering), nor minimizes LCC (which is done by Operations), demonstrating the difference between the risk and the average-case criteria.

Finally, note that for $\varepsilon < 0.77\%$, the Supply, Engineering and Operations solutions comprise a Pareto set, and a post hoc criteria weighting technique would be required to choose between them.

4.2.2. Cross-domain solutions

To investigate the potential to improve the single-domain solution we allocate resources across domains, and take partial solutions from each domain. We start by examining an equal allocation across the 4 domains, and then examine unequal allocations. In each case, we seek an alternative which is superior to the best single-domain 1%-ε solution (Supply).

We begin by examining a scenario which implements 25% of each of the four proposed single-domain alternatives. Note that we are not claiming the cost of doing this would be the same as implementing one of the single-domain solutions. Indeed, because of the fixed costs of implementing any of the changes suggested in the scenarios, we believe it will likely cost more. However, proponents of 'breaking silos' have claimed large improvements are possible by encouraging cross-domain solutions.

Table 4 shows the equal allocation results. Implementing 25% of the improvement in each of the four domains does improve performance compared to the Status Quo, but it does not provide a better 1%-ε solution, nor does it provide a the greatest reduction in LCC, readiness risk, or cost risk, nor does it provide the greatest increase in Ao.

Next, we increased the equal allocation percentage in 1% increments (from 25% to 26%, etc.) to determine the smallest equal-percentage allocation that would produce a solution superior to the single-domain 1%-ε solution. Table 3 shows the result of that search. Each domain must implement at least 43% of their proposed changes before an equal-allocation scenario is superior to the best single domain 1%-ε solution. However, with 43% of changes in all domains implemented, our test for dominance indicates CD-43% $\prec_{iz}$ Supply ($\chi^2_{df=1} = 782.7$, $p < 0.000$).

So, with these scenarios, if we allocate equally we must allocate more resources (at least 72% more) to a cross-domain solution than a single domain solution, to provide superior results.

It might be argued that this is a 'straw-man' demonstration. Because one solution is better than another, it will 'obviously' be better to allocate resources to the best domain. Note that for a

Table 3
Status Quo performance, and single-domain alternatives.

Scenario	LCC	Ao (%)	\$-risk (%)	Ao risk (%)	\$r-stdv (%)	Aor-stdv (%)
Status Quo	5,979,351,957	79.3	6.46	21.04	0.06	0.11
Engineering	5,879,512,821	82.7	3.18	5.65	0.05	0.06
Operations	5,865,943,764	80.8	4.58	14.81	0.05	0.09
Maintenance	5,951,263,687	80.0	4.80	15.72	0.06	0.09
Supply	5,915,427,985	82.5	3.95	4.49	0.05	0.05

Table 4
Equal allocation cross-domain scenarios compared to best single-domain scenario.[a]

Scenario	LCC	Ao (%)	$-risk (%)	Ao risk (%)	$r-stdv (%)	Aor-stdv (%)
Status Quo	5,979,351,957	79.3	6.46	21.04	0.06	0.11
Supply	5,915,427,985	82.5	3.95	4.49	0.05	0.05
CD-43%	5,866,786,776	82.8	2.94	3.98	0.04	0.05
CD-42%	5,867,788,257	82.7	2.97	4.20	0.04	0.05
CD-25%	5,910,938,751	81.5	4.01	9.40	0.05	0.08

[a] Status Quo is incorporated for convenience. Supply is the best single-domain alternative. The CD-XX% alternatives are constructed by allocating XX% of the budget requested to *each* domain.

bi-criteria problem, this is not so obvious: no single domain provides the best increase in both risk criteria (or in the averages). So, we wanted to determine how easily a better cross-domain solution could be obtained without allocating more resources (i.e., limiting allocation across domains to 100%), if we relaxed the equal-allocation restriction. Do determine this, conducted a search of the possible scenarios, allowing unequal allocation of the percentage-change across domains, but restricting the total percentage-change to 100%.

Of course there are an infinite number of such scenarios, so we needed a sampling strategy. We chose to sample the state space by examining only 5% increments of each domain-change, while maintaining the restriction that the total change implemented across the four domains must total 100%. This is only a heuristic sampling plan: because the response surface is non-linear, we may miss a dominant alternative. Still, this search space contains 1771 scenarios (the same as the number of ways to distribute 20 nickels to 4 individuals (Jackson & Thoro, 1989, p. 103)). And our goal in this cross-domain search is not to develop an efficient non-linear optimization search procedure. Rather, we are trying to (1) investigate the robustness of the finding that cross-domain solutions are not necessarily better for these scenarios and (2) demonstrate the importance of a cross-domain model when allocating resources for cross-domain solutions (i.e., the more difficult it is to find such a solution, the more important it is to have a model).

Table 5 contains the 22 scenarios we found out of 1771 for which were indifferent (at $\varepsilon = 1\%$) to the Supply scenario. Each cross-domain scenario in the table is indicated by four numbers, representing the four respective percentages allocated to each domain, Engineering, Supply, Maintenance and Operations.

No solution was found which dominated the supply scenario at $\varepsilon = 1\%$. The single-domain supply scenario is surprisingly robust. At $\varepsilon = 0.5\%$, even the scenarios marked with an asterisk are dominated by it. Below $\varepsilon = 0.5\%$, we no longer have a unique solution, but multiple scenarios form a Pareto Set.

Among the 1771 scenarios investigated for this example, solutions that are 1%-ε indifferent to the best single-domain solution involve no more than 5% allocation to Operations, no more than a 10% allocation to Maintenance, no more than a 35% allocation to Engineering, and at least a 65% allocation to Supply.

We contend that an allocation procedure which did not have a cross-domain model such as the one we have used in this example would be unlikely to arrive at such an unequal allocation across the four domains, especially if the allocation was guided by qualitative factors and sensitive to political considerations.

5. Summary, limitations and extensions

This paper has contributed to the work on the management of LCC and Ao for complex systems in two important ways. First, we developed an approach for ranking and selection which accounts for correlation between the criteria, rather than a descriptive or decision support approach. To our knowledge, this is the first approach to ranking and selection for this bi-criteria problem. Second, we examine the issues of logistic *silos* in the management of complex systems, and the degree to which they may cause sub-optimal results. As briefly reviewed above, this is a significant issue in public management, but ours is among the only research which attempts to quantify the issue.

Table 5
Unequal allocation cross-domain scenarios with total allocation constrained. Bolded values indicate local optima.

Scenario	LCC	Ao (%)	$-risk (%)	Ao risk (%)	$r-stdv (%)	Aor-stdv (%)
Status Quo	5,979,351,957	79.3	6.46	21.04	0.06	0.11
Supply	5,915,427,985	82.5	3.95	**4.49**	0.05	0.05
5-95-0-0	5,913,240,821	82.5	3.97	4.60	0.05	0.05
10-90-0-0	5,908,802,855	82.5	3.89	4.56	0.05	0.05
5-90-5-0	5,915,202,983	82.4	3.99	4.93	0.05	0.06
5-90-0-5*	5,914,598,108	82.4	4.00	5.09	0.05	0.06
15-85-0-0	5,908,773,348	82.5	3.71	4.64	0.05	0.06
5-85-10-0*	5,916,470,468	82.2	4.01	5.29	0.05	0.06
10-85-5-0*	5,911,054,431	82.4	3.88	5.09	0.05	0.06
10-85-0-5*	5,909,235,724	82.4	3.90	5.11	0.05	0.06
20-80-0-0	5,906,351,335	82.5	3.71	4.81	0.05	0.06
15-80-5-0*	5,911,515,834	82.4	3.83	5.07	0.05	0.06
15-80-0-5*	5,907,809,325	82.4	3.81	5.14	0.05	0.06
10-80-10-0*	5,913,819,825	82.3	3.96	5.34	0.05	0.06
10-80-5-5*	5,911,990,400	82.3	3.92	5.49	0.05	0.06
25-75-0-0	5,902,291,980	82.6	3.62	4.73	0.05	0.05
20-75-5-0*	5,908,981,656	82.4	3.86	5.12	0.05	0.06
20-75-0-5*	5,905,446,492	82.4	3.78	5.14	0.05	0.06
30-70-0-0	5,903,100,225	82.6	3.77	4.85	0.05	0.06
25-70-5-0*	5,907,081,142	82.4	3.78	5.19	0.05	0.06
25-70-0-5*	5,905,180,472	82.4	3.73	5.25	0.05	0.06
35-65-0-0*	5,899,708,555	82.6	**3.57**	5.03	0.05	0.06
30-65-5-0*	5,904,988,515	82.4	3.68	5.32	0.05	0.06
30-65-0-5*	5,901,601,534	82.5	3.71	5.40	0.05	0.06

In looking at risk metrics as criteria (rather than average LCC and average Ao) we took the perspective of stewardship, which we define as the goal is to keep one's promises over the life of the assets. We recognize the fact that in today's economic environment, cost reduction is a primary concern, rather than risk reduction. However, good stewardship (which we define as minimizing the risk that cost and availability thresholds will not be met) is still important. One of the contributions of this paper was the development of a model to support the stewardship perspective.

An objection may be raised to our stewardship criteria along the following lines: Given a choice between a reduction in average cost, and a reduction in the risk of exceeding the promised cost (without a reduction in average cost), what principal would prefer his agent to choose the latter? But the reduction in average cost must come with a relative *increase* in the risk that cost will exceed the promised threshold (otherwise, the steward would also prefer the first choice). In this light, the choice for the principal is a classic risk/return tradeoff. While the precise formulation of this risk/return choice is well beyond the scope of the current paper, we simply point out that the public sector investor (i.e., the taxpayer) is notoriously risk averse. And finally, risk analysis is valuable in public investments even if stewardship is not admitted to be the primary criteria, because given the imprecise nature of the data in many public investments, a risk analysis provides a more robust examination of possible, rather than just expected outcomes.

Our numerical analysis only investigated a single set of scenarios, so it not possible to generalize about cross-domain solutions to process improvement problems even in this one system, let alone complex systems in general. But at a minimum, we intend our numerical analysis to be a sort of counter-example to the idea that cross-domain 'silo breaking' solutions are always superior. However, we also intend the analysis to be a demonstration of the fact that the system wide impact of even single-domain solutions requires an integrative system-level model to predict. The discussion of cross-domain solutions is really a discussion in the dark without such a model, at least in complex systems. Yet many complex systems are managed without such models. Still it remains a limitation of this paper that we have only used our model to analyze a single set of scenarios.

Another limitation of this paper is that, although we have developed a ranking and selection method to choose between alternatives, we have not developed an optimization procedure that can be used to search for the best alternative possible. Still, we believe our model and procedure are incremental contributions in the direction of the development of a global optimization procedure.

One of the extensions needed for the current work is a more careful examination of when risk minimization is an appropriate objective. We have simply assumed that it is synonymous with good stewardship. We think this is a reasonable assumption in an organization where cost and availability targets are set at one level of a hierarchy, but those targets must be met operationally by a lower level of the hierarchy. We also believe that the quantification of risk via a model such as the one we have developed is important even when risk minimization is not a primary objective. But further investigation is needed to determine the relative advantages of other ways of looking at mean/risk tradeoffs in managing complex assets.

While the case example we have used in this paper revolves around a weapon system, we believe our results have wider implications. Models examining LCC and Ao have been developed for the energy sector for example (e.g., Bouachera, 2012; Jin et al., 2003), and a method of jointly minimizing the readiness and cost risk of process improvement investments may be useful in those industries as well.

That cross-domain, cooperative solutions are not easy to find in complex systems, and that detailed cross-domain models must support such efforts is also an important idea that has implications beyond public management, to the management of large private sector firms as well. At least, our case example highlights the fact that people must be careful when they talk about 'breaking down silos' or cooperative, cross-domain solutions. Such solutions are not likely to involve an equal allocation of resources: it is likely that they are difficult to implement precisely because the domain-managers understand that the cooperative solution may involve giving up resources to another domain. It is also likely that, absent tools such as the one presented in this paper, the cooperative solutions that are chosen are unlikely to go to the manager with the greatest opportunity to use them, but may instead go to the manager who is most persuasive. Research is needed to assess the cost of this 'trial by combat' method of cooperation, and to assess whether the cost of developing integrated system models, such as the one presented in this paper, might be justified in order to facilitate a more productive method of cooperation.

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